The Effects of Unemployment on Crime Rates in the U.S.

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Abstract

This paper aims to analyze the relationship between unemployment and crime rate. Using data from 2013 acquired from the Federal Bureau of Investigation (used for violent crime rate data) and from the Bureau of Labor Statistics (used for unemployment data), the effect of unemployment rate on violent crime is estimated. In addition to unemployment rate, GDP per capita, high school graduation rates, police officers per 100,000 inhabitants, as well as poverty rates also are accounted for. Two equations are present, one which estimates the variable's impacts on violent crime, and another for their impacts on property crime. In both the simple and multiple regression models for estimated the enumerated variables' impacts on crime rate, the results were that there were positive effects of these variables on the crime rate. From this, it can be concluded that there is a positive correlation between both violent and property crime, not only with unemployment rate, but also with GDP per capita, high school graduation rates, police officers per 100,000 inhabitants, and poverty rate.

I. Introduction

There is a common conception that irregularities in the business cycle lead to higher crime rates. Since the world is still recovering from the worst recession since the Great Depression in the 1930s, this correlation is more than relevant. Recessions, the peak of a trough in the business cycles, occur when the economy is contracting. This leads to a loss of jobs on a wide-scale. The unemployment rate is one of the best indicators of the health of our economy. High unemployment brings frustration to the consumer due to a loss of disposable income. The standard of living for most falls greatly, which puts great pressure to maintain the lifestyle accustomed to. After 2007, the unemployment rose steadily, peaking at an annual average of 10% in 2009, which was 5% higher than the average the four years prior.[1]

In this paper, we chose to examine the relationship between criminal activity and the unemployment rate. We hypothesize that higher unemployment leads to higher crime rates. Our judgement was supported by the fact that the cities in the United States with the highest crime rates all have a population below poverty rate higher than the U.S. average of 15.1%.[2] Detroit has the highest reported violent crime rate of 2,072/100,000 people, with 38.1% of their population living below the poverty line.[3]

The idea is that those without a steady income have a greater incentive to commit crimes than those with a steady income, who may have more to lose if caught. Understanding the relationship between criminal activity and prime variables such as unemployment, poverty, density of the police force, GDP, and high school graduation rates, will allow us to plan the most effective way to make our country, as a whole, a safer place to live. The ability to lower crime rates nationwide will bring about many benefits such as increased domestic and foreign investment, better overall quality of education and housing, as well as a reduction in inequality.

[1] BLS spotlight on Statistics: The Recession of 2007-2009
[2] Crime in America 2015: Top 10 Most Dangerous Cities Over 200,000
[3] Crime in America 2015: Top 10 Most Dangerous Cities Over 200,000

II. Literature Review

Crime, Job Searches, and Economic Growth

Chang and Wu (2012) are both well-known and widely published economic academics. *Crime, Job Searches and Economic Growth* was published in a reputable journal—The Atlanta Economic Journal, which is the official publication of the Atlanta Economic Society, and has been exploring economic issues of interest for more than thirty years. Their article references a variety of previously published case studies and standing economic theories related to crime and unemployment, as well as relevant statistics in order to lend credibility to their research and conclusions.

The piece considers a significant amount of data—each theory and conclusion is accompanied by data and extensive analysis in order to explain how specific conclusions were reached. The goal of the paper is to analyze the link between unemployment and crime rates; the most convincing proposition put forth by the authors was that "an increase in the average crime rate in the economy or a high probability of detecting crime leads to a decrease in the employment rate in the labor market due to a reduction in the number of vacancies offered by firms."[4] This logical conclusion is subsequently supported by appropriate statistical analysis. The authors do, however, put forth the somewhat confusing proposition that those who are employed and unemployed are both equally likely to commit a crime. The data supporting this conclusion is somewhat conflicting, because a certain portion of the authors' data supports the conclusion that the relationship between unemployment and growth rates is procyclical, while a different section supports the conclusion that the relationship between the two variables is counter-cyclical.

Overall, the arguments put forth in this article are convincing and, most importantly, are supported by a wide range of data. Given the seemingly conflicting nature of some of the propositions detailed in the article, it is clear that the authors have presented a very unbiased look at their data and research.

[4] Chang, J., & Wu, C. (2012). Crime, Job Searches, and Economic Growth. *Atlantic Economic Journal*.

An Examination of the Link between Employment Volatility and the Spatial Distribution of Property Crime Rates

Bausman (2004) is an Assistant Professor of Sociology and the Criminology Program Coordinator at Maryville University of Saint Louis. He focuses his studies on the variations in impact of social and economic restrictions on crime patterns across metropolitan and nonmetropolitan communities. His work has appeared in *Rural Sociology, Human Ecology Review and Rural Development Perspectives.* Goe (2004), a professor of Sociology in the Department of Sociology, Anthropology, and Social Work at Kansas State University, has research that appeared in Social Forces, Urban Affairs Review and Growth and Change.

The article, *An Examination of the Link between Employment Volatility and the Spatial Distribution of Property Crime Rates,* discusses how recent research has produced inconsistent findings of the relationship between economic marginalization and the spatial distribution of crime rates. The reason is because economic marginalization focuses solely on unemployment and poverty, while ignoring other contributing factors. They argue that employment volatility represents an important source of economic marginalization. Their hypothesis is tested using a regression processes to analyze the effects of employment volatility measures on the correlations of property crime across 683 U.S. metropolitan counties from 1980-1983.[5] Their findings suggest that high levels of employment volatility are needed to maintain higher levels of property crime in general.

Research finds that deindustrialization, and the transition into a service-based economy, is an important factor associated with high levels of crime, and that crime occurs in higher rates inner-city neighborhoods. The findings recognize the correlation between employment volatility and criminal activity, but urges not to overemphasize this correlation, because while employment volatility is a factor of crime rates, it is by no means a primary one.

Inequality, Unemployment and Crime: A Cross-National Analysis

This article analyzes inequality, unemployment and crime rates internationally. Krohn hypothesizes that nations with high rate of unemployment and unequal distribution of income have high rates of crime.

[5]An Examination of the Link between Employment Volatility and the Spatial Distribution of Property Crime Rates

The research studies three relationships: the relationship between social class and crime, the effect of fluctuations in the business cycle on the crime rate, and the influence of unemployment on crime. There is much controversy surrounding the first relationship and the research regarding this relationship is not conducted in this article. The assumption is that there is a clear inverse relationship between social class and crime rates, in terms of self-reported data, for serious offenses. For petty offenses, however, there is no significant relationship. The second relationship has had many contradicting findings. Using data from the Great Depression in the U.S. in 1927, Krohn concluded that there is not a strong correlation between the economic situation and rates of crime. But, analysis from Poland during the depression concluded that there is an inverse relationship between economic conditions and crime.[6] The research on the last relationship was also inconsistent and some suggested it was because data on juveniles and adults were combined.[7] Since this analysis, there have been few international studies on unemployment and crime, and those show little to no significant relationship between these variables.

The arguments discussed above show that the research on the relationship between unemployment and inequality on crime is not conclusive.

Identifying the Effect of Unemployment on Crime

Raphael (2001) of the University of California at Berkeley and Winter-Ebmer (2001) of the University of Linz and Center for Economic Policy Research in London analyze – with OLS regression – the relationship between unemployment and crime using state-level data for the period of 1971-97 for each U.S. state. The dependent variable is the crime rate, which is divided into two categories: property crime (burglary, larceny, and auto theft) and violent crime (murder, rape, robbery, and assault). A relatively straightforward hypothesis emerged from their analysis: there is a positive correlation between the crime rate and unemployment. In other words, individuals are incentivized to participate in illegal activities, as the relative return for doing so is higher than the decrease in income with unemployment. Indeed, Raphael and Winter-Ebmer found a relatively significant, positive effect of unemployment on property crime rates.[8] Yet, the

[6] Inequality, Unemployment and Crime: A Cross-National Analysis
[7] Inequality, Unemployment and Crime: A Cross-National Analysis
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effect of unemployment on violent crime rates wasn't so clear. In fact, with murder and rape, the predicted effects of unemployment were negative.

Our analysis will emerge from the core foundation of this study by examining effects of state-level unemployment rates on both property crime rates and violent crime rates. However, instead of analyzing the effects on each specific crime, we are going to focus on the effects on aggregate property and violent crime rates. Also, in minor deviation from this study, we are going to include GDP per capita, high school graduation rates, poverty rates, and number of police officers per 100,000 inhabitants in our multiple regression.

III. Data

For the simple regression analysis, the crime rates (property crime and violent crime per 100,000 inhabitants) for each state for 2013 (n=50) was selected as the dependent variable while the unemployment rate for each state for 2013 was selected as the independent variable.

$$propcrimerte = \beta_0 + \beta_1(unemprate) + u$$
$$vlntcrimerte = \beta_0 + \beta_1(unemprate) + u$$

While violent crime contains four separate categories: murder, rape, robbery, and aggravated assault; however, our regression will use the aggregate violent crime rate per 100,000 inhabitants for each state. Similarly, property crime contains three separate categories: burglary, larceny, and motor vehicle theft; yet, our regression will utilize the aggregate property crime rate per 100,000 inhabitants for each state. The violent crime rates for each state were acquired from the Federal Bureau of Investigation's Uniform Crime Reporting System while the unemployment rates for each state were obtained from the Bureau of Labor Statistics.

For the multiple regression analysis, in addition to unemployment, four other independent variables were included: GDP per capita, high school graduation rates, number of police officers per 100,000 inhabitants, and poverty rates.

$$propcrimerte = \beta_0 + \beta_1(unemprate) + \beta_2(gradrate) + \beta_3(gdpPerCapita) + \beta_4(totalpolice) + \beta_5(povrate) + u$$
$$vlntcrimerte = \beta_0 + \beta_1(unemprate) + \beta_2(gradrate) + \beta_3(gdpPerCapita) + \beta_4(totalpolice) + \beta_5(povrate) + u$$

Real GDP per capita (chained in 2009 dollars) for 2013 was acquired for each state from the Bureau of Economic Analysis. High school graduation rates were obtained from the National Center for Educational Statistic for the 2012-13 school year for each state. The aggregate number of police officers per state was acquired from the Federal Bureau of Investigation Uniform Crime Reporting System for 2009. Poverty rates were obtained from the Census Bureau, specifically, the percentage of people in poverty per state using three year averages from 2011-13. The reasoning behind including economic indicators such as GDP per capita, poverty rate, and the unemployment rate is relatively straightforward; the less well off an individual may be, the more enticed he or she may be to commit a crime. The inclusion of the number of police officers and educational attainment (high school graduation rate), on the other hand, can be somewhat less economically intuitive. Yet, one could conclude that more police officers would disincentivize criminal behavior while a higher educational attainment could imply more legal income-generating opportunities , thus, less time for criminal behavior. **Figure 1** displays the basic statistics for each variable within the single and multiple regression models analyzed in this study.

Figure 1: Summary Statistics

Variable	# of Observations	Mean	Standard Deviation	Minimum	Maximum
propcrimerte	50	2698.58	557.35	1824.8	3710.3
vlntcrimerte	50	349.1	124.856	121.1	640.4
unemprate	50	6.734	1.54	2.9	9.5
gradrate	50	79.9	12.76	0*	90
gdpPerCapita	50	48,183.42	9237.31	32421	70113
totalpolice	50	288.94	50.40	155.09	405.75
povrate	50	14.096	3.171	8.3	21.4

*Idaho did not report graduation rate for data

The assumption of linearity in parameters is satisfied since our model can be written as $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + u$. The assumption of random sampling is satisfied as we used all available population data from each variable analyzed. The assumption of no perfect

collinearity is satisfied as there are no perfect linear relationships among the independent variables. **Figure 2** (below) shows there are no perfect linear relationships between our independent variables in the simple and multiple regression models. The assumption, zero conditional mean, is satisfied as the error *u* has an expected value of zero for any values of the independent variables. Furthermore, the assumption of homoskedasticity is satisfied because the error term has the same variance with any value of the independent variables. Therefore, our regression models satisfy the Gauss-Markov assumptions.

Figure 2: Correlation

	propcrimetre	**vlntcrimerte**	**unemprate**	**gradrate**	**gdpPerCapita**	**totalpolice**	**povrate**
propcrimetre	1.0000						
vlntcrimerte	0.5409	1.0000					
unemprate	0.1968	0.3936	1.0000				
gradrate	0.0122	-0.0397	-0.1208	1.0000			
gdpPerCapita	-0.3136	-0.0082	-0.2347	0.1950	1.0000		
totalpolice	-0.0305	0.2039	0.2018	0.1358	0.1520	1.0000	
povrate	0.5657	0.4803	0.4982	-0.1971	-0.5744	0.1359	1.0000

IV. Results

The results (OLS coefficients, t-values, t-tests (2-tailed), intercepts, number of observations, and R^2) of our simple and multiple regression models - for *propcrimerte* and *vlntcimerte* - are listed below in **Figure 3**.

Figure 3: Regression Results

Independent Variables	Simple (propcrimerte)	Simple (vlntcrimerte)	Multiple (propcrimerte)	Multiple (vlntcrimerte)
unemprate (unemployment rate)	71.13419 (1.39)	31.87251*** (2.97)	-31.99244 (-0.63)	14.24473 (1.25)
gradrate (high school graduation rate)	N/A	N/A	6.328355 (1.16)	.2472923 (0.20)
gdpPerCapita (real GDP per capita)	N/A	N/A	.0031239 (0.34)	.0050586** (2.44)
totalpolice (total police per 100,000 inhabitants)	N/A	N/A	-1.474965 (-1.03)	.0626536 (0.20)
povrate (poverty rate)	N/A	N/A	120.635*** (4.05)	23.98936*** (3.60)
Intercept	2219.558*** (6.28)	134.4725* (1.81)	895.0726 (1.07)	-362.8174* (-1.94)
Observations	50	50	50	50
R^2	0.0387	0.1549	0.3604	0.3630

(*) reject null at 10% level of significance
(**) reject null at 5% level of significance
(***) reject null at 1% level of significance

Simple Regression Model for Property Crime Rates

Resulting from a simple regression analysis, the following equation shows the estimated effects of unemployment on property crime rates for each U.S. state (n=50).

$$propcrimerte = 2219.558 + 71.13419\ unemprate$$

The regression of unemployment on property crime rates generates a positive coefficient of 71.13419. In other words, a one percent increase in the the unemployment rate will increase the property crime rate by 71.13419 per 100,000 inhabitants.

Simple Regression Model for Violent Crime Rates

Resulting from a simple regression analysis, the following equations shows the estimated effects of unemployment on violent crime rates for each U.S. state (n=50).

$$vlntcrimerte = 134.4725 + 31.87251\ unemprate$$

The regression of unemployment on violent crime rates generates a positive coefficient of 31.87251, and is statistically significant at the 10% level. A one percent increase in the unemployment rate will increase the violent crime rate by 31.87251 per 100,000 inhabitants.

Multiple Regression Model for Property Crime Rates

Resulting from a multiple regression analysis, the following equation shows the estimated effects of unemployment, high school graduation rates, GDP per capita, # of police per 100,000 inhabitants, and poverty rate on property crime rates for each U.S. state (n=50).

$$propcrimerte = 895.1 - 31.9\ unemprate + 6.3\ gradrate + .00312\ gdpPerCapita - 1.475\ totalpolice + 120.64\ povrate$$

Surprisingly, a one percentage point increase in the unemployment rate will decrease the property crime rate by 31.9 per 100,000 inhabitants. Similarly, a one percentage point increase in the high school graduation rate will increase the property crime rate by 6.3 per 100,000

inhabitants, indicating people commit crimes regardless of educational attainment, at least at the high school level. A unit increase in GDP per capita will increase the property crime rate by .00312 per 100,000 inhabitants. A unit increase in the number of police officers per 100,000 inhabitants will decrease the property crime rate by 1.475 per 100,000 inhabitants. A one percent increase in the poverty rate will increase the property crime rate by 120.64 per 100,000 inhabitants, and is statistically significant at the 1% level.

Multiple Regression Model for Violent Crime Rates

From a multiple regression analysis, the following equation shows the estimated effects of unemployment, high school graduation rates, GDP per capita, number of police per 100,000 inhabitants, and poverty rate on violent crime rates for each U.S. state (n=50).

$$vlntcrimerte = -362.82 + 14.3\ unemprate + .247\ gradrate + .0051\ gdpPerCapita + .063\ totalpolice + 23.9\ povrate$$

A one percent increase in the unemployment rate will increase the violent crime rate by 14.3 per 100,000 inhabitants. A one percent increase in the high school graduation rate will increase the violent crime rate by .247 per 100,000 inhabitants. Surprisingly, a unit increase in GDP per capita will increase the violent crime rate by .0051 per 100,000 inhabitants, and is statistically significant at the 5% level. A unit increase in the number of police officers per 100,000 inhabitants will increase the violent crime rate by .063 per 100,000 inhabitants, which is somewhat counterintuitive as one would think that more law enforcement officers would lower violent crime. A one percent increase in the poverty rate will increase the violent crime rate by 23.9 per 100,000 inhabitants, and is statistically significant at the 1% level.

Test for Robustness: F-test

In order to determine how robust our models were, we conducted a F-test. The unemployment and poverty rate variables had a high correlation of 0.4982 suggesting they could have a linear relationship. We removed both these variables in our restricted model (see below) and used this equation:

$$F = \frac{(R^2_{UR} - R^2_R)/q}{(1 - R^2_{UR})/(n-k-1)}$$

The f-statistic for property crime was 3.38 and 5.46 for violent crime rate. Both these f-statistic values are higher than the critical value of 2.61 determined the 44 degrees of freedom. Our results show that we should reject the null hypothesis H_0, at the 5% level of significance meaning that they are jointly significant. The equation for the restricted model is shown below, and the results of our unrestricted and restricted models are also found below in **Figure 4**.

Restricted Model

$$propcrimerte = \beta_0 + \beta_1(gradrate) + \beta_2(gdpPerCapita) + \beta_3(totalpolice) + u$$
$$vlntcrimerte = \beta_0 + \beta_1(gradrate) + \beta_2(gdpPerCapita) + \beta_3(totalpolice) + u$$

Results

Figure 4: Regression Results with Restricted Model

Independent Variables	Unrestricted (propcrimerte)	Unrestricted (vlntcrimerte)	Restricted (propcrimerte)	Restricted (vlntcrimerte)
unemprate	-31.99244 (-0.63)	14.24473 (1.25)	N/A	N/A
gradrate	6.328355 (1.16)	.2472923 (0.20)	3.287987 (0.53)	-.6215356 (-0.43)
gdpPerCapita	.0031239 (0.34)	.0050586** (2.44)	-.0198967** (-2.30)	-.0003886 (-0.19)
totalpolice	-1.474965 (-1.03)	.0626536 (0.20)	.1046716 (0.07)	.5372918 (1.48)
povrate	120.635*** (4.05)	23.98936*** (3.60)	N/A	N/A
Intercept	895.0726 (1.07)	-362.8174* (-1.94)	3370.592*** (5.29)	294.4749* (2.00)
Observations	50	50	50	50
R^2	0.3604	0.3630	0.1041	0.0470

(*) reject null at 10% level of significance
(**) reject null at 5% level of significance
(***) reject null at 1% level of significance

V. Conclusion

Analyzing the relationship between unemployment and crime rate, we hypothesized that there would be a positive correlation which our results support. For both the simple and multiple regression models, there were positive effects of the variables on crime rate. In the simple model, the unemployment rate had a positive effect on both property and violent crimes as expected. There was a surprise in our multiple regression model; the unemployment rate had a negative effect on property crime and a smaller positive effect on violent crime than the simple model, which can be accounted for by the introduction of new variables that affect crime rates.

We believe the reason for the negative effect of unemployment on property crime rates was the influence of poverty rates. But variables are highly correlated, and our results show that we reject the null hypothesis for poverty rate at a 1% level of significance. And after testing for robustness, we concluded that both unemployment rate and poverty rates were jointly significant.

Our results support our hypothesis that lower economic status, specifically higher unemployment leads to higher crimes rates, both property and crime. The introduction of more police officers does deter violent crime some, but the greatest indicator of crime rates out of all the variables we tested was poverty rates.

VI. References

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VII. Appendix

STATA output for simple regression model (*propcrimerte*):

Source	SS	df	MS	Number of obs =	50
				F(1, 48) =	1.93
Model	589560.211	1	589560.211	Prob > F =	0.1707
Residual	14631816.6	48	304829.512	R-squared =	0.0387
				Adj R-squared =	0.0187
Total	15221376.8	49	310640.343	Root MSE =	552.11

propcrimerte	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
unemprate	71.13419	51.14967	1.39	0.171	-31.70911	173.9775
_cons	2219.558	353.1809	6.28	0.000	1509.44	2929.676

STATA output for simple regression model (*vlntcrimerte*):

Source	SS	df	MS	Number of obs =	50
				F(1, 48) =	8.80
Model	118359.743	1	118359.743	Prob > F =	0.0047
Residual	645498.847	48	13447.8926	R-squared =	0.1549
				Adj R-squared =	0.1373
Total	763858.59	49	15588.9508	Root MSE =	115.97

vlntcrimerte	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
unemprate	31.87251	10.74339	2.97	0.005	10.27148	53.47355
_cons	134.4725	74.18155	1.81	0.076	-14.6795	283.6245

STATA output for multiple regression model/**unrestricted** (*propcrimert*e):

Source	SS	df	MS		
Model	5486068.46	5	1097213.69	Number of obs	= 50
Residual	9735308.33	44	221257.007	F(5, 44)	= 4.96
				Prob > F	= 0.0011
Total	15221376.8	49	310640.343	R-squared	= 0.3604
				Adj R-squared	= 0.2877
				Root MSE	= 470.38

propcrimerte	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
unemprate	-31.99244	50.98428	-0.63	0.534	-134.7445	70.75961
gradrate	6.328355	5.467325	1.16	0.253	-4.690314	17.34702
gdpPerCapita	.0031239	.0092878	0.34	0.738	-.0155944	.0218421
totalpolice	-1.474965	1.434244	-1.03	0.309	-4.365495	1.415564
Povrate	120.635	29.80847	4.05	0.000	60.56002	180.7101
_cons	895.0726	837.1865	1.07	0.291	-792.1659	2582.311

STATA output for multiple regression model/**unrestricted** (*vlntcrimerte*):

Source	SS	df	MS		
Model	277255.205	5	55451.041	Number of obs	= 50
Residual	486603.385	44	11059.1678	F(5, 44)	= 5.01
				Prob > F	= 0.0010
Total	763858.59	49	15588.9508	R-squared	= 0.3630
				Adj R-squared	= 0.2906
				Root MSE	= 105.16

vlntcrimerte	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
unemprate	14.24473	11.39853	1.25	0.218	-8.727501	37.21697
gradrate	.2472923	1.222327	0.20	0.841	-2.216147	2.710731
gdpPerCapita	.0050586	.0020765	2.44	0.019	.0008737	.0092434
totalpolice	.0626539	.3206534	0.20	0.846	-.5835805	.7088884
Povrate	23.98936	6.664268	3.60	0.001	10.55841	37.42031
_cons	-362.8174	187.1694	-1.94	0.059	-740.0326	14.39778

STATA output for multiple regression model/**restricted** (*propcrimerte*):

Source	SS	df	MS		
Model	1583934.26	3	527978.085		
Residual	13637442.5	46	296466.142		
Total	15221376.8	49	310640.343		

Number of obs	=	50		
F(3, 46)	=	1.78		
Prob > F	=	0.1640		
R-squared	=	0.1041		
Adj R-squared	=	0.0456		
Root MSE	=	544.49		

propcrimerte	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
gradrate	3.287987	6.25421	0.53	0.602	-9.301086	15.87706
gdpPerCapita	-.0198967	.008658	-2.30	0.026	-.0373244	-.0024689
totalpolice	.1046716	1.570855	0.07	0.947	-3.057296	3.266639
_cons	3370.592	637.6923	5.29	0.000	2086.984	4654.2

STATA output for multiple regression model/**restricted** (vlntcrimerte):

Source	SS	df	MS		
Model	35885.3214	3	11961.7738		
Residual	727973.268	46	15825.5058		
Total	763858.59	49	15588.9508		

Number of obs	=	50		
F(3, 46)	=	0.76		
Prob > F	=	0.5247		
R-squared	=	0.0470		
Adj R-squared	=	-0.0152		
Root MSE	=	125.8		

vlntcrimerte	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
gradrate	-.6215356	1.444986	-0.43	0.669	-3.530142	2.287071
gdpPerCapita	-.0003886	.0020004	-0.19	0.847	-.0044151	.003638
totalpolice	.5372918	.3629338	1.48	0.146	-.1932561	1.26784
_cons	294.4749	147.3338	2.00	0.052	-2.092685	591.0424